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A study on smart parking guidance algorithm

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ABSTRACT

Parking problem becomes one of major issues in the city transportation management since the spatial resource of a city is limited and the parking cost is expensive. Lots of cars on the road should spend unnecessary time and consume energy during searching for parking due to limited parking space. To cope with these limitations and give more intelligent solutions to drivers in the selection of parking facility, this study proposes a smart parking guidance algorithm. The proposed algorithm supports drivers to find the most appropriate parking facility considering real-time status of parking facilities in a city. To suggest the most suitable parking facility, several factors such as driving distance to the guided parking facility, walking distance from the guided parking facility to destination, expected parking cost, and traffic congestion due to parking guidance, are considered in the proposed algorithm. To evaluate the effectiveness of the proposed algorithm, simulation tests have been carried out. The proposed algorithm helps to maximize the utilization of space resources of a city, and reduce unnecessary energy consumption and CO_2 emission of wandering cars since it is designed to control the utilization of parking facility efficiently and reduce traffic congestion due to parking space search.

1. Introduction

Originally, an automobile (hereafter a car) was invented to increase convenience and comfort in everyday life. However, the car congestion in a big city causes undesirable problems such as environmental issues, energy consumption, parking space shortage, traffic jams, noise, air pollution, and even minor psychological damage to some people. Among them, the parking space shortage is regarded as one of major issues in the city transportation management since the spatial resource of a city is limited and the construction cost of new parking is expensive. As a result, many cars on the road should spend unnecessary time and consume extraneous energy during searching for parking spaces. According to the recent research work (Giuffrè et al., 2012) dealing with the significance of parking problem, the traffic flow peak caused by searching parking facilities can increase as much as about 25–40%. Arnott et al. (2005) mentioned that about 30% of cars on the road in the downtown area of major cities seemed to be cruising for parking spots, which took an average of 7.8 min. The other study (Soup, 2007) found that the wandering of cars in order to find a parking facility is responsible for about 30% of the entire traffic in a city. Soup (2007) summarized the annual waste of resources to find a parking lot in a city of LA, USA, as shown in Table 1. Furthermore, Caliskan et al. (2007) cited from a study of parking situation in Schwabing (a district of Germany) that an annual total economy damage had been estimated as 20 million euro, caused only by the traffic searching for free parking lots.

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Table 1
Annual waste of resources to find a parking lot in Westwood Village, LA 2007 (Soup, 2007).

Item	Figure	Remarks
Cruising distance	950,000 miles	38 trips around the earth or four trips to the moon
Waste of time	95,000 h	11 years
Waste of gasoline	47,000 gallons	177,660 l
CO_2 production	730 tons	

Due to the significance of parking problem, various technical developments to resolve it have been introduced and implemented until so far. For example, the parking guidance and information system (PGIS) is the most frequently adopted solution in many cities. Generally, the PGIS has a form of message board which is installed on the road to help wandering drivers who try to find parking facilities. The rough direction and number of free parking lots at each parking facility are provided to drivers by the message board. Based on the PGIS message board, drivers can decide which parking facility they will use. However, the provided information by the message board may be not valuable when drivers actually arrive at the parking facility since the number of free parking lots on the sign may be changed during driving. Furthermore, the form of message board is inappropriate to provide drivers with detailed direction to each parking facility. The information delivered by PGIS message board is limited so that it is impossible to provide personalized information such as which parking facility is the closest from a driver to destination, which parking facility is cheaper than others, and how a driver can avoid traffic jam while heading to the guided parking facility. In summary, the PGIS as a form of message board is not suitable for providing the smart parking guidance considering dynamic situations of both parking facilities and traffic conditions. Due to these shortcomings, the impact of PGIS system as a form of message board may be relatively limited from the viewpoint of reducing the car wandering time for searching parking space (Thompson and Bonsall, 1997; Waterson et al., 2001).

To cope with these limitations and give more intelligent solution to drivers in the selection of parking facility and direction guidance, this study introduces the concept of smart parking guidance system and proposes a parking guidance algorithm to assign the car requesting parking space to the most appropriate parking facility considering driving duration and distance to parking facility, walking distance from parking facility to destination, expected parking cost, and traffic congestion due to parking guidance itself. According to Caicedo's work (2010), the real-time parking information management could improve 10% of traffic in efficiency. Based on this result, the considering smart parking guidance system is designed to be operated in the real-time environment. In the proposed system, the real-time monitoring of parking lot status is performed by sensors, and the monitored status data are collected and transferred through wire/wireless telecommunication network. All data collected from both parking facilities and cruising cars are integrated and managed by the central server for smart parking guidance. The proposed parking guidance algorithm is designed to maximize the utilization of spatial parking resource of a city, to reduce unnecessary energy consumption and CO_2 emission of wandering cars, to improve drivers' satisfaction, and to alleviate traffic congestion due to parking guidance itself.

This study is organized as follows. The following section introduces previous research works related to parking management systems. The detailed procedure of the parking guidance algorithm to assign the car requesting parking space to the most suitable parking facility is explained in Section 3. Section 4 validates the proposed algorithm with simulation tests. Finally, it ends with conclusion and discusses on the development for smart parking guidance system.

2. Previous works

The application of various information and communication technologies (ICTs) in everyday urban life makes it possible to realize the concept of smart city. In general, the smart city is identified as the following characteristics: smart economy, smart people, smart governance, smart mobility, smart environment, and smart living (The Centre of Regional Science, 2007). Among them, the smart mobility is one of the most fast-growing areas using various ICTs actively, and a well-known example for smart mobility is the intelligent transport system (ITS). The ITS collects real-time information of road status and controls traffic adaptively. According to the traffic status, traffic lights are changed automatically so that the overall traffic can be adjusted so as not to be congested. Smart parking combined with ITS can play an important role in achieving the concept of smart mobility. The smart parking guidance based on the real-time information of parking lot in the city can be available within the smart city. However, the current status of smart parking guidance is still in its infancy. The integration of ICTs and efficient information management to enhance parking guidance still remains as challenging issues. Considering that parking problem is one of the complicated issues in a big city and its limited availability can cause the quality deterioration of urban mobility, it is important to improve the current parking guidance approach in an intelligent way. This section will review the previous research efforts to provide parking guidance and discuss about pros and cons of their works.

2.1. ICTs for smart parking

To monitor the availability of parking lots, various kinds of sensors and sensor network technologies have been developed, and some of them are already available as commercial products in the market. Most of them are designed and used

to check the status of parking lots in an indoor environment. For example, the parking space locators system (ParkSens) developed by Boston University presented a method to sense the occupancy status of a parking lot with a magnetic sensor by detecting the fluctuation of magnetic field. For the data communication, Caliskan et al. (2007) introduced a vehicular ad hoc network (VANETs) which is used to transfer the status information of parking lot and proposed an application of VANETs into parking facility management. Based on these developments of ICTs, some commercial systems for the indoor parking management become available in the market. For example, the Siemens parking management (called SIPARK) developed by Siemens can provide a guidance to lead drivers to the empty parking space in a parking building. The single space detection (SSD) system of SIPARK monitors every single parking lot using ultrasonic detectors and guides entered car with LED arrow and zone/numeric screens to the next free parking lot. Some airports such as OR Tambo Airport (South Africa) and JFK Airport (US) have provided real-time information on available parking spaces to drivers. In these parking guidance systems, electronic signs to provide the information on parking availability of different parking facilities or within a parking facility are used. The ultrasonic LED sensors are mostly used detecting sensors for car presence of parking space. For the outdoor parking space, a wireless magnetometer is considered. The XALOC developed by University of Barcelona tried to combine a parking guidance system with a personal mobile information device (e.g. iPAD) in order to improve accessibility of parking information. To extend parking lot monitoring from indoor to outdoor, Seong-Eun et al. (2008) have developed a more robust wireless sensor network against harsh outdoor environment in checking the occupancy of a parking lot. The conceptual system architecture of parking guidance system based on the developed sensor and its network have been also proposed in their work. As a recent application of intelligent parking management system in the real field, San Francisco (city of USA) builds a new system called 'SFpark pilot' program, which helps drivers who are seeking for parking space. In this program, drivers can check the availability of parking spaces through Internet. The smartphone applications have been also recently developed and available in the market. For example, Seoul (city of Korea) developed a mobile application on Android environment to provide real-time free parking information. In USA, the mobile application named 'Parker 4.0' was released in 2013. This application provides real-time parking information such as availability of on-street and garage/lot parking, cost, and operation hour. In spite of convenience and accessibility of parking information through mobile application, the decision support to find the best parking place is still missing and remains as a challenging issue.

In summary, thanks to these previous efforts, it becomes possible to monitor the status of parking lot and collect related information remotely from both indoor and outdoor in a real-time way. However, most parking management systems are restricted to a single building. The parking data for drivers on the road from the viewpoint of city are still limited since most provided information could be obtainable by only a message board. Although the SIPARK of Siemens developed dynamic message signs to provide information on the current occupancy levels of individual parking area, and tried to combine multiple parking facilities, the available information and guidance for the smart parking guidance are still primitive. Furthermore, although the access to the parking information becomes easier and convenient due to smart phone applications, there is still the lack of supporting drivers in the choice of the best parking. Most smart parking systems in the market stays are in its early stage so that it is necessary to realize an intelligent parking guidance.

2.2. City parking guidance based on a message board

Unlike the parking management system for a single parking facility, that for a city is more complicated. Various characteristics such as the degree of traffic congestion during driving to a guided parking facility, unexpected situation while driving to a guided parking facility, comparisons of driving distances or parking cost among parking facilities, and other factors related to the decision of parking choice, should be considered in the parking management for a city. The current PGIS based on the message board could not consider these factors in parking guidance. In spite of its limitations, the effectiveness of the parking management system for a city cannot be underestimated. Waterson et al. (2001) illustrated the potential of PGIS to induce the parking demand to spread more efficiently across the parking spaces using the driver parking choice model. The message board provides necessary information for the parking choice model. According to whether a driver has experience to visit a city or not, the different parking choice model is used in the selection of parking facility. For the drivers who know the city, expected chance of having queue for more than 5 min in front of parking facility, usage experience of the parking facility, walking time, and cost have been considered. To change the route from the selected parking facility during driving, expected drive time, expected wait time based on the queue of parking facility, the most recently updated number of spaces by PGI sign, and so on, have been used. The parking cost and estimated current queuing time outside parking facility are selected as considering factors of the drivers who have no experience on the city. These factors are formulated as utility function of parking facility, which is used to evaluate and select a parking facility. The utility function is implemented for the simulation test to quantify the effectiveness of parking guidance.

In many cases, the general application of parking management for a city is to install the PGIS with a form of message board. Its role is to show the number of available parking lots within some area and brief direction to each parking facility. Considering the aim of PGIS, the most important thing is to provide drivers with the highest possibility to find free parking lots when they arrive at the guided parking facility. To this end, some research works have focused on the improvement of the reliability of PGIS. For example, Thompson et al. (2001) developed a behavioral model of parking choice in order to predict the influence of PGI signs and to provide the most efficient information for free parking lots. In their work, like Waterson et al. (2001), the dis-utility function was used in the selection of parking facility. In this function, value of time, car travel time, waiting time at parking, parking cost, and walking time were considered. Using the dis-utility function, the probability

for a driver to choose a particular parking facility with or without information on PGI signs was calculated. Then, the calculated probability was used to estimate the arrival rates of cars at each parking facility. According to the display time configuration of PGI signs, the arrival rates can be varied so that it is required to find optimal configuration. To do this, a mathematical program was formulated with two kinds of objectives such as minimal queue length and minimal vehicle kilometers of travel. To solve it, a genetic algorithm was applied. On the other hand, to consider real-time road environment, Shi et al. (2004) suggested the real-time and dynamic PGIS providing dynamic guidance. Fuzzy clustering analysis was used to categorize drivers, and parking lots were assigned to drivers considering drivers' preferences. According to the drivers' preferences, the drivers could be dynamically grouped and assigned to different parking lots, which would avoid congestion to a particular parking lot. Moreover, Mei et al. (2012) introduced a concept of guiding parking reliability of urban parking variable message signs (VMSs). Based on the analysis of parking choice, a guiding parking reliability model was defined as a mathematical program model to determine the reliability of guiding parking with VMS.

Although the current PGIS based on message board increases the possibility of finding parking space, it still has several shortcomings (Yanfeng and Cassandras, 2011; Geng and Cassandras, 2012) as follows: (1) there is no guarantee that drivers can find vacant parking spots by following the guidance, (2) even if a driver is successfully guided to a parking spot, there could be any missing opportunity to find better parking spot while heading to the guided parking spot, and (3) from the traffic authority point of view, there could be imbalance of the degree of utilization among parking facilities due to the lack of parking congestion management. Although it is true that the PGIS based on message board gives better possibility for drivers to find free parking lots, the usefulness of message board is restricted and it cannot provide personalized guidance to drivers. To improve the parking management for a city, the more smart parking guidance that can consider dynamic parking and traffic factors needs to be developed.

2.3. Smart parking management system

Due to the limitations of PGIS based on VMS, a smart parking guidance system has been introduced to provide drivers with more useful information. For example, Song and Wen (2011) introduced an extended concept of urban parking guidance system based on the message board. In their work, a framework of parking guidance information system was introduced, and the necessary entities and processes for parking guidance were described. Furthermore, Giuffrè et al. (2012) proposed a conceptual architecture of intelligent parking assistant (IPA) to provide parking management solutions for street parking facilities. The proposed model in their work consists of five modules: parking space controller, communication module, user interface module, manager interface, and function module. Using sensor network, the availability for parking space was being checked, and drivers could reserve the free parking lot with the proposed IPA system.

On the other hand, to improve parking management, various methods have been studied. For example, Benenson et al. (2008) developed an agent-based, spatially explicit model in order to simulate parking in a city. In their model, the behaviors of drivers were defined and used to show the impact of additional parking supply in a residential area. Some research works focused on the improvement of the reliability of parking guidance. For example, Caliskan et al. (2007) focused on the improvement of prediction of free parking lots. They developed a system to monitor the occupancy status of parking lots and implemented the prediction model for lot occupation. The prediction of free parking lot is done by homogeneous Markov model with exponentially distributed inter-arrival and parking time. The usefulness of their model has been shown by simulation test. Moreover, some works dealt with parking selection considering several factors related to it. For example, Leephakpreeda (2007) proposed a car-parking guidance model using fuzzy knowledge-based decision making. In this model, the best parking facility in a building was decided considering distance to building entrances, car safety, shade from sunlight outdoors, and so on. To improve parking guidance, a new process such as on-line reservation has been also adopted in parking management system. The bay area rapid transit (BART), in San Francisco/Oakland metropolitan area, has been developed as a centralized intelligent reservation and real time availability system which provides parking availability via telephone and internet. According to a report published by Wilbur-Smith Associates (2009), the on-line reservation of BART could improve customer experience and satisfaction. Teodorović and Lučić (2006) also introduced a reservation function in an intelligent parking system. Depending on the different parking tariff class, the "on-line" decisions regarding the acceptance or rejection of driver requests were made using simulation, optimization technique, and fuzzy logic. Using reservation function, they developed a parking space inventory control model to maximize the revenue of a parking operator. Geng and Cassandras (2012) also adopted a reservation concept and presented a new smart parking system based on wireless network. They dealt with an optimal allocation problem of parking lot considering parking cost and distance to destination. They applied a queuing model in order to resolve the optimal allocation problem in their work. In the selection of proper parking facility, several factors have been considered concurrently. Hanif et al. (2010) introduced a new reservation system enabling parking reservation through short message service (SMS). The usefulness of reservation system was proved by the work done by Hongwei and Wenbo (2011). In their work, the smart parking system based on reservation was introduced and it was shown that the reservation-based parking guidance had the potential to simplify parking operation and to reduce traffic congestion by parking searching. Hensher and King (2000) focused on the demand studies regarding parking. In their work, some attributes have been introduced and used in the decision of parking place. Behavioral responses of a driver, parking price, parking location relative to final destination, the nature of guarantee on a parking space are the mainly considered factors in the decision. In addition, Thompson et al. (2001) used queue length and vehicle kilometers of travel as the objective function of parking guidance and information system.

From the perspective of parking guidance, the most primitive approach is 'Blind Search'. The 'Blind Search' approach is based on a simple strategy applied by drivers when no parking information is provided. In this strategy, drivers keep cruising for parking spaces within a certain distance to their destination and stop searching until they find free parking space. Since there is no available information regarding current status of parking and traffic under the blind search, drivers have the low opportunity to find free parking lot so that the redundant trials to find free parking occur. Another approach is 'Parking Information Sharing (PIS)'. In this case, the information on parking availability is provided to drivers in a certain area. Using this information, drivers decide designated parking place. This approach works well when the number of available parking lots is enough. However, as the number of free parking lots becomes decreasing, the drivers having parking information can increase traffic congestion to certain parking lots, which is called 'multiple-car-chasing-single-space'. To solve this problem caused by PIS, the 'Buffered PIS (BPIS)' is proposed. Within the BPIS approach, the intentionally reduced number of free parking lots is provided in order to keep buffer and the reserved buffer can relieve the congestion caused by 'multiple-car-chasing-single-space'. However, this method has the difficult in deciding the size of the buffer on the parking lot. According to the buffer size, the 'multiple-car-chasing-single-space' phenomenon can occur or the utilization of parking spaces becomes low. On the other hand, Yanfeng and Cassandras (2011) and Geng and Cassandras (2012) proposed a parking guidance from the viewpoint of the car parking allocation. Furthermore, Benenson et al. (2008) developed the agent-based model to choose parking based on the rule implemented in the simulation. Chou et al. (2008) also used an agent-based platform in the parking guidance. However, unlike the Benenson et al. (2008)'s work, the parking guidance was performed by the negotiation between drivers and parking based on parking price. In the developed system, the parking is suggested to drivers considering proximity to destination and parking cost, and overall parking capacity. Some research works are interested in the driver's behavior in choosing parking place, which is called 'parking choice behavior model'. Most works have proposed the utility function composed of several factors that affect parking choice (Bonsall and Palmer, 2004; Jonkers et al., 2011; and Mei et al., 2010). In the previous works to improve parking guidance, we know that various kinds of factors are considered in the parking choice under different system environments and the objectives of parking management are diverse. In spite of these different approaches, it is still lack of considering dynamic parking environment in the provision of parking guidance.

Even though many cities in China, Japan, Europe, and United states operate PGIS (Thompson and Bonsall, 1997) and intelligent parking reservation (IPR) systems as a part of intelligent transportation system (ITS), the implementation of smart parking guidance for a city is still in its infancy. Most previous research works are related with the generation of parking information based on message board. There is lack of research works dealing with the parking guidance system with dynamic information gathered by ICTs. The emerging ICTs make it possible to collect updated real-time parking information such as parking location, capacity, parking fee, current utilization or availability, and performance of specific on-street parking or off-street parking facilities. Combining with real-time data of parking information and drivers' needs, more intelligent parking guidance can be provided. On the other hand, the parking guidance system for a city should consider not only drivers' benefits but also overall efficiency of parking resources in a city. Until now, less of works dealt with the parking guidance considering both aspects. To cope with these limitations, this study will propose a method to provide smart parking guidance considering several factors which affect the assignment of cars to parking facilities.

3. Smart parking guidance algorithm

To provide the smart parking guidance in a city area where many cars are simultaneously searching for parking places, it is necessary to assign each car to the most appropriate parking facility in an efficient way, which is the purpose of the smart parking guidance algorithm. In general, there will be many car drivers which simultaneously request parking guidance on the road. Furthermore, the status of availability on parking lots changes frequently so that the huge amount of data processing makes it difficult to find optimal assignment solutions in response to drivers' requests. Hence, it is necessary to find the most appropriate parking facilities for all requesting cars in a real-time way and an efficient manner. To this end, the proposed algorithm assigns each car to the suitable parking lot with a dispatching rule. The dispatching rule is based on the evaluation of the values of two kinds of parking utility functions proposed in this study. The proposed parking utility functions assess the assignment decision of the requesting car to a certain parking facility. The assignment of the requesting car to a certain parking facility should be done considering dynamic characteristics of parking environment such as parking facility utilization, traffic condition, user convenience, and so on. To this end, the proposed parking utility functions consider several dynamic factors (e.g. duration from current location to a certain parking facility, walking distance from a certain parking facility to destination, parking cost, probability of availability, and traffic congestion caused by parking guidance). The values of the utility functions are used to select the most appropriate parking facility. The detailed procedure will be explained in the following subsections.

3.1. Overall scenario

In the considering system, there are five objects; (1) parking lot, (2) parking management system, (3) central server, (4) personal navigation device, and (5) driver. The installed sensor on each parking lot checks its parking availability continuously. Whenever the parking lot status changes, it is transferred to the parking management system. The parking

management system collects all the status of parking lots in a parking facility and sends the collected information to the central server through wire/wireless telecommunication. As soon as the information of parking lot status from each parking facility is transmitted to the central server, it is updated and stored in the database of the central server. Later the collected information is used for the parking guidance algorithm in the central server. The parking guidance is triggered by the driver's request through personal navigation device in a car. On the screen of the personal navigation device, a driver inputs his/her destination, and then, the parking request with necessary information used in the selection of a parking facility is transmitted to the central server. The transmitted information from the personal navigation device are, for example, current location of the car requesting parking, destination, driving duration and distance from current car to parking facilities near destination, and walking distance from parking facilities to the destination. The parking guidance algorithm operated in the central server evaluates each parking facility from the viewpoint of each driver's parking preference and selects the most appropriate parking facility based on the current status of parking lots and the information obtained from the personal navigation device. The selected parking facility by the parking guidance algorithm is suggested to the driver through the personal navigation device. The driver can reserve the specific parking lot until he or she arrives at the suggested parking facility or just drive to the suggested parking facility without reservation. If the driver reserves the specific parking lot, the parking cost occurs from the reservation time. When the driver arrives at the guided parking facility (or the front of the reserved parking lot), the status of parking facility are updated and sent to the central server through the parking management system. The detailed procedure of smart parking guidance system is depicted as shown in Fig. 1.

3.2. Smart parking guidance algorithm

The flow chart in Fig. 2 shows the detailed procedure to assign the car requesting parking to the suitable parking facility. The procedure describes the interactions among three main objects: parking facility, central server, and car driver. The parking facility monitors each parking lot continuously and sends the information on its status change to the central server whenever any change occurs. A car driver triggers the parking guidance system by requesting parking through a personal navigation device in a car. Then, the necessary data to evaluate and select the most appropriate parking facility, e.g. travel distance from the current car location to a certain parking facility, walking distance from the parking facility to the destination, are calculated in the personal navigation device and transferred to the central server. The central server calculates the value of utility function of each parking facility. The proposed algorithm provides car drivers with the smart parking guidance with two steps: the first step is to provide a car driver with the reservation option. It suggests a parking lot in the most suitable parking facility for reservation. The second step is to suggest the most suitable parking facility without reservation. In the first step, according to the value of *parking utility function for reservation*, it is decided whether the reservation option will be provided to the driver or not. This decision is based on the comparison of the value of the utility function with a threshold value. The threshold value is set to avoid suggesting unsatisfactory parking facilities to the driver. When the value of the utility function is lower than the threshold value, the reservation option is provided to the driver. With this option, the driver can decide whether he/she reserves a certain parking lot until he/she arrives at the parking lot. If the driver accepts the reservation option, the suggested parking lot is reserved until the driver arrives and subsequently parking cost occurs from that time. If the driver refuses to reserve the parking lot or the value of *parking utility function for reservation* is higher than the threshold value, the value of the second utility function called *parking utility function for suggestion* is calculated to find the next most appropriate parking facility. Among parking facilities, the parking facility which has the lowest value of *parking utility function for suggestion* is suggested to the driver and the detailed direction guide to the suggested parking facility is provided through personal navigation device. When the car requesting parking arrives at the reserved or suggested parking facility, the status of parking facility is changed and the database of the central server is updated. This procedure is repeated whenever the request for car parking comes to the central server.

The more detailed description of the proposed procedure is as follows:

Step 1. Keep the current status of parking lot availability of all parking facilities in a city.

To assign the cars requesting parking to proper parking facilities, it is important to keep the current status of parking lot availability as up-to-date in the database. Each parking lot of a parking facility is monitored by the sensor and the status data of its availability is collected by the parking management system. The parking management system keeps track of the vacancy status of each parking lot and sends the number of free parking lots to the central server. As soon as the central server receives the data from parking management systems, it updates the database which records all the number of free parking lots of parking facilities in a city. In addition to the number of free parking lots, other data related to parking facility such as parking capacity, and parking cost, required for parking assignment are also stored in the database. The stored data are updated whenever changes happen in parking facilities.

Step 2. The request of parking guidance is triggered by a driver.

The request of parking guidance is triggered by a driver through the personal navigation device in a car. To request parking guidance, a driver inputs his/her destination on the screen of personal navigation device. Since the personal navigation device has the GPS module inside, the geological location of a car is obtained automatically. Considering the destination of the driver, the personal navigation device finds parking facilities near the destination. Then, driving

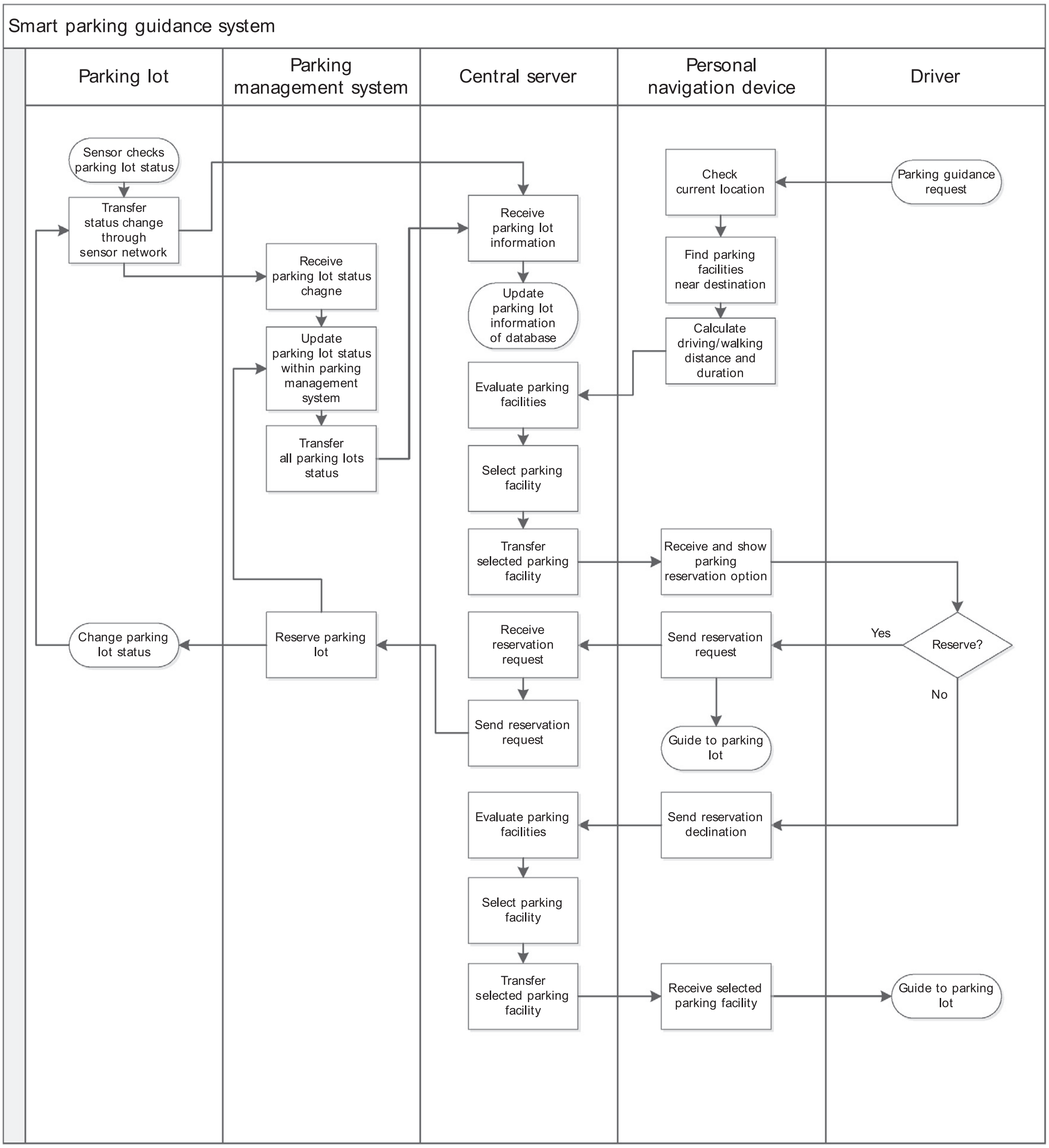

Fig. 1. Overall procedure of smart parking guidance system.

duration and distance from the driver to each parking facility, and walking distance from each parking facility to the destination are calculated by the navigation software installed in the personal navigation device. The current location of a driver, destination, driving distances and durations of parking facilities, and walking distance are sent to the central server.

Step 3. For each parking facility, calculate the value of *parking utility function for reservation*.

To evaluate and select the proper parking facility, two kinds of parking utility functions are used. In the first step, the *parking utility function for reservation* is calculated. The *parking utility function for reservation* evaluates each parking facility from the viewpoint of reservation benefit of a driver since a driver may want to reserve a parking lot in order to secure it until he or she arrives at the parking facility. The *parking utility function for reservation* is based on a kind of generalized cost function (Thompson et al., 2001) in order to consider multiple factors influencing the choice of parking facility. According to previous works (Shi et al., 2004; Lam et al., 2006; Caicedo et al., 2012; Hensher and King, 2000), walking distance to destination, driving and waiting time, parking fees, and service level of parking lots, safety, guaranteeing

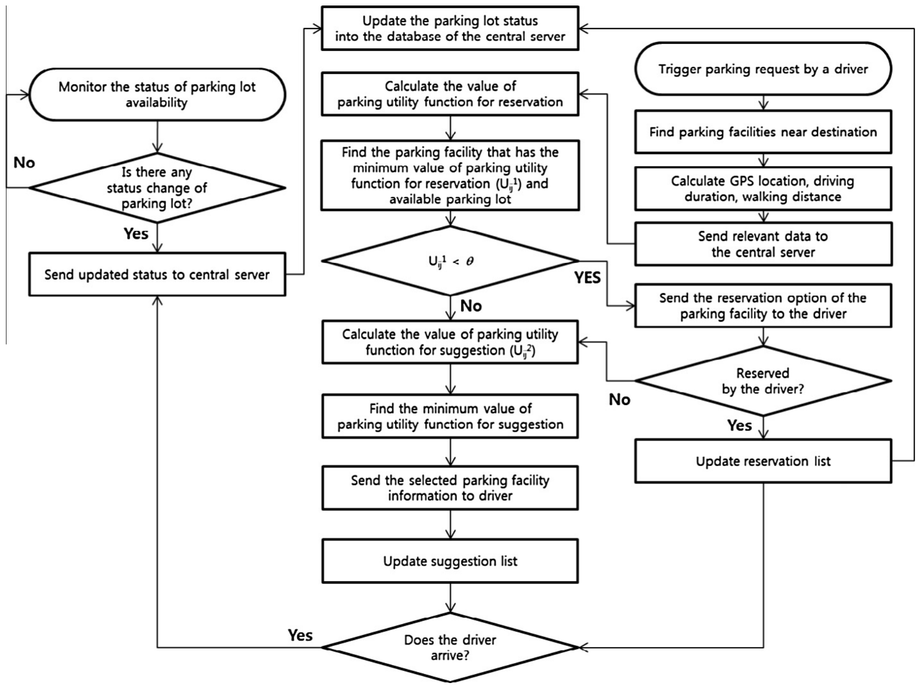

Fig. 2. Overall procedure of parking guidance algorithm.

optimal accessibility, optimal traffic flow and minimum nuisance from parked cars, maximizing turn-over for shops, and minimizing the use of the private car in a city, and so on, are examples of factors considered by drivers when they select the parking place. Among various factors, this study chooses four factors in order to calculate the value of *parking utility function for reservation*: (1) driving duration from current car location to a parking facility, (2) walking distance from a parking facility to destination, (3) parking cost, and (4) traffic congestion caused by parking guidance itself. The first three factors are commonly used in previous works. In addition, this study considers traffic congestion caused by parking guidance in order to deal with not only drivers' benefit but also the efficiency of spatial resource of a city concurrently. The *parking utility function for reservation* is defined as the weighted sum of four factors. Here, the weighting value for each factor can have three values (1, 2, 3) depending on the degree of its importance. The defined *parking utility function for reservation* is expressed as Eq. (1).

$$U_{ij}^1 = (\alpha_1 T_{ij}^* + \alpha_2 W_{ij}^* + \alpha_3 C_j^* + \alpha_4 P_j^*)/12 \tag{1}$$

where

- i index of car i (i = 1,. . .,n)
- j index of parking facility j (j = 1,. . .,m)
- n the number of the cars requesting parking in a certain area
- N the maximum number of the cars requesting parking in simulation test
- m the number of parking facilities in a certain area
- U_{ij}^1 parking utility function for reservation of the car i to the parking facility j, ($0 \leqslant U_{ij}^1 \leqslant 1$)
- T_{ij} estimated driving duration from current location of the car i to the parking facility j
- T_{ij}^* normalized value of T_{ij} by all parking facilities ($T_{ij}^* = (T_{ij} - T_{ij}^{\min})/(T_{ij}^{\max} - T_{ij}^{\min})$ where $T_{ij}^{\max}$ and $T_{ij}^{\min}$ are maximum and minimum values of T_{ij}'s, respectively, j = 1,. . .,m, $0 \leqslant T_{ij}^* \leqslant 1$)
- W_{ij} walking distance from destination of the car i to the parking facility j (j = 1,. . .,m)
- W_{ij}^* normalized value of W_{ij} by all parking facilities ($W_{ij}^* = (W_{ij} - W_{ij}^{\min})/(W_{ij}^{\max} - W_{ij}^{\min})$, j = 1,. . .,m, $0 \leqslant W_{ij}^* \leqslant 1$)
- C_j parking cost of parking facility j (Euro/hour)
- C_j^* normalized value of C_j by all parking facilities ($C_j^* = (C_j - C_j^{\min})/(C_j^{\max} - C_j^{\min})$, j = 1,. . .,m, $0 \leqslant C_j^* \leqslant 1$)
- P_j the number of cars heading to the parking facility j according to parking guidance at a certain time (the degree of traffic congestion)
- P_j^* normalized value of P_j by all parking facilities ($P_j^* = (P_j - P_j^{\min})/(P_j^{\max} - P_j^{\min})$, j = 1,. . .,m, $0 \leqslant P_j^* \leqslant 1$)
- α_1 weighting factor for driving duration from current car position to the guided parking space (α_1 = 1,2,3)

α_2 weighting factor for walking distance from the guided parking space to destination (α_2 = 1,2,3)
α_3 weighting factor for parking cost (α_3 = 1,2,3)
α_4 weighting factor for the degree of traffic congestion (α_4 = 1,2,3)
θ threshold value for comparing the value of parking utility function for reservation

Driving duration and walking distance are calculated using GPS data in a personal navigation device. Parking cost of each parking facility is stored in the database of the central sever. The value of P_j is calculated in the central server. The value of P_j is added in order to consider the degree of traffic congestion sprang from parking guidance itself. As the more cars are guided to a specific parking facility, the traffic congestion near this parking facility will increase so that the number of the guided cars to a specific parking facility is added as a factor to measure the degree of traffic congestion. This factor helps to avoid the situation that too many cars are heading to the same parking facility simultaneously. Before calculating the value of *parking utility function for reservation*, the value of each factor is normalized from zero to one since the scale of each factor is different. After normalization, the values of *parking utility function for reservation* of *i*th car to all parking facilities are calculated and compared. The lower value of parking utility function means that the parking facility has less driving duration to the destination, more closer walking distance to destination, lower parking cost, and less traffic congestion. Since the parking cost is charged from the reservation time, the parking lot with the low value of *parking utility function for reservation* is more preferable. If the values of utility function are the same in two facilities, the randomly selected facility is proposed to the driver.

Step 4. Reserve a parking lot or go to Step 5 without reservation.

The calculated values of the *parking utility function for reservation* of parking facilities using Eq. (1) are sorted in an ascending order. From the parking facility with the lowest value, it is checked whether the value is lower than threshold value 'θ', and there is an available free parking lot or not. The threshold value is set so as not to charge too much cost of reservation. If the parking facility which has the lowest value of *parking utility function for reservation* does not satisfy the conditions of threshold and free parking lot constraints, the parking facility which has the next lowest value is considered. This checking continues until the parking facility has a lower value than threshold, and simultaneously it has the available free parking lot. If there is a feasible parking facility, the reservation option for the parking facility is provided to the driver through the personal navigation device. On the screen of personal navigation device, the found parking facility and related information such as the overall cost, driving duration, and walking distance as well as reservation button are displayed. The driver can decide whether he/she will reserve this parking lot or not based on this information. In case that the driver wants to reserve the parking lot, he/she can tab the button on screen of personal navigation device and reservation request is sent back to the central server. The central server transfers the reservation request to the parking management system of the selected parking facility. Using reservation option, the driver can secure parking lot until he/she arrives.

Step 5. For each parking facility, calculate the value of *parking utility function for suggestion*.

In the case that a driver does not want to reserve the suggested parking lot in advance or there is no available free parking lot at the moment of parking guidance requesting, the next most appropriate parking facility should be suggested. To do this, the second parking utility function called the *parking utility function for suggestion* is defined in this study. Unlike the *parking utility function for reservation* case, this case cannot guarantee the parking lot for the guided parking facility since the status of parking lots of the guided parking facility could change before he/she arrives. Considering this circumstance, we define *parking utility function for suggestion* which recommends the best parking facility for a driver considering five factors. Among five factors, three factors are the same as those of the *parking utility function for reservation*. In the *parking utility function for suggestion*, unlike using driving duration at the *parking utility function for reservation*, the driving distance from the current location to each parking facility is considered. Since the driving duration can be varied by traffic condition in spite of the same driving distance and the driving duration is charged as parking cost, the driving duration is selected as a factor of the *parking utility function for reservation*. However, in the *parking utility function for suggestion*, the parking cost is not considered as an important factor for selecting the parking facility since the parking cost does not occur until the car parks at the selected parking facility, and it could be assumed that there is no difference on the parking cost according to parking facilities in a certain area of a city. Instead of driving duration, the driving distance is mostly considered as a decision factor of parking selection in other previous works. Thus, in this study, the driving distance instead of driving duration is also considered as one decision factor to select the appropriate parking facility.

In addition to driving distance factor, to increase the possibility to find a free parking lot when a driver arrives at the guided parking facility, the *parking utility function for suggestion* considers another factor called the *degree of availability* for each parking facility. To increase the possibility to find a free parking lot when a driver arrives at the guided parking facility, it is desirable that less cars use the suggested parking facility. To know the extent of how frequently cars visit and occupy the specific parking facility, the mean time between arrivals (MTBA) is calculated for each parking facility. The MTBA represents how frequently cars arrive at the parking facility. The defined MTBA is formulated by Eq. (2).

$$MTBA_j = \frac{\sum_{k=2}^{q_j}(t_{jk} - t_{j(k-1)})}{q_j - 1} \quad (2)$$

where

$MTBA_j$	mean time between car arrivals of the parking facility j (j = 1,. . .,m) at a certain time interval
k	index of car arrivals for the parking facility j until a certain time interval (k = 1,. . .,q_j)
t_{jk}	the kth car arrival time at the parking facility j (j = 1,. . .,m)
q_j	the number of cars arrived at the parking facility j at a certain time period (j = 1,. . .,m)

Using $MTBA_j$, the expected number of arriving cars to the parking facility j during driving of the car i toward the parking facility j can be estimated. The low value of $MTBA_j$ means that cars arrive frequently. Then, the ratio between the expected number of arriving cars and the number of free parking lots at the jth parking facility at a certain time, called *the degree of availability* for the parking facility j, R_{ij}, can be calculated by Eq. (3).

$$R_{ij} = \frac{\frac{T_{ij}}{MTBA_j}}{f_j} \quad (3)$$

f_j indicates the number of free parking lots of parking facility j at a certain time t. The lower value of R_{ij} indicates that it is more likely to find the free parking lot when a driver arrives at parking facility j since less cars are expected to come compared to the number of free parking lots.

The equation of *parking utility function for suggestion* is defined as Eq. (4).

$$U_{ij}^2 = (\beta_1 D_{ij}^* + \beta_2 W_{ij}^* + \beta_3 C_j^* + \beta_4 P_j^* + \beta_5 R_{ij}^*)/15 \quad (4)$$

where

U_{ij}^2	*parking utility function for suggestion* of the car i to the parking facility j ($0 \leqslant U_{ij}^2 \leqslant 1$)
D_{ij}	estimated driving distance from current location of the car i to the parking facility j
D_{ij}^*	normalized value of D_{ij} by all parking facilities ($D_{ij}^* = (D_{ij} - D_{ij}^{\min})/(D_{ij}^{\max} - D_{ij}^{\min})$, j = 1,. . ., m, $0 \leqslant D_{ij}^* \leqslant 1$)
W_{ij}	walking distance from the destination of the car i to the parking facility j (j = 1,. . ., m)
W_{ij}^*	normalized value of W_{ij} by all parking facilities ($W_{ij}^* = (W_{ij} - W_{ij}^{\min})/(W_{ij}^{\max} - W_{ij}^{\min})$, j = 1,. . ., m, $0 \leqslant W_{ij}^* \leqslant 1$)
C_j	parking cost of the parking facility j (Euro/hour)
C_j^*	normalized value of C_j by all parking facilities ($C_j^* = (C_j - C_j^{\min})/(C_j^{\max} - C_j^{\min})$, j = 1,. . ., m, $0 \leqslant C_j^* \leqslant 1$)
P_j	the number of the cars heading to the parking facility j according to parking guidance (the degree of traffic congestion)
P_j^*	normalized value of P_j by all parking facilities ($P_j^* = (P_j - P_j^{\min})/(P_j^{\max} - P_j^{\min})$, j = 1,. . ., m, $0 \leqslant P_j^* \leqslant 1$)
R_{ij}^*	normalized value of R_{ij} by all parking facilities ($R_{ij}^* = (R_{ij} - R_{ij}^{\min})/(R_{ij}^{\max} - R_{ij}^{\min})$, j = 1,. . ., m, $0 \leqslant R_j^* \leqslant 1$)
β_1	weighting factor for driving distance from current car position to the guided parking lot (β_1 = 1,2,3)
β_2	weighting factor for walking distance from the guided parking lot to destination (β_2 = 1,2,3)
β_3	weighting factor for parking cost (β_3 = 1,2,3)
β_4	weighting factor for the degree of traffic congestion (β_4 = 1,2,3)
β_5	weighting factor for the degree of availability (β_5 = 1,2,3)

All factors are normalized in the same way as the *parking utility function for reservation* does. The value of weighting factor can be given as 1 (Neutral) or 2 (Important) or 3 (Very important) depending on the degree of its importance. The values of parking utilities calculated by Eq. (4) are sorted in an ascending order. The parking facility which has the lowest value of *parking utility function for suggestion* is selected as the most appropriate parking facility and provided to the driver through the personal navigation device. If the values of utility function are the same in two facilities, the randomly selected facility is proposed to the driver. The personal navigation device guides the driver to the selected parking facility with detailed directions.

Step 6. Repeat step 2–5 for all parking requesting cars.

4. Simulation result

4.1. Experimental environment

For the analysis and evaluation of the proposed algorithm, a discrete time based simulation has been performed considering real world spatial environment. The simulation test case is taken from a city of Luxemburg since Luxemburg has a

serious parking problem due to traffic congestion and limited parking area. In addition, Luxemburg has the highest vehicle ownership rate (394,917 vehicles including motor cycles from 502,000 inhabitants in 2011) in the world, which makes the parking problem in a city center area very worse. The target test area of Luxemburg is depicted in Fig. 3. The locations of the cars requesting parking are randomly generated within this area. The destination of each car is also randomly generated within the dotted area in Fig. 3 (6 × 12 km). The area of destination generation is narrowed to the central city area since the city center shows more high parking demand and the effect of smart parking guidance in congested area shows better effect. The driving distance and duration from a car to each parking facility, and walking distance from each parking facility to destination are calculated using Google map service to consider the real environment.

The 13 parking facilities in the city center are selected and used for the simulation. The GPS data of each parking facility is gathered from the geographical information system (GIS) of Google map as shown in Fig. 3. The capacity of each parking facility is generated based on the information of Luxemburg city guide (see Table 2) to increase the reality of simulation. The parking cost (euro/hour) is arbitrarily set considering variations. The number of cars that have been already parked in the beginning of simulation is randomly generated.

The simulation has been run under the following assumptions;

(1) Once a driver decides to go to the suggested parking facility, the driver does not change the designated parking facility.
(2) The driving duration in simulation is the same as that estimated by Google map calculation.
(3) The effect on the increase of driving duration by traffic congestion is not considered in this study.

4.2. Simulation parameters

The simulation has been performed in order to evaluate the effectiveness of the proposed smart parking guidance algorithm at the Luxemburg city. The total simulation time is set to 4 h and the unit simulation time is set to each minute (totally 240 min). In the real world, the parking request occurs in continuous time domain. However, our simulation works in discrete time domain by minute in order to reduce calculation burden. The population of Luxemburg is about 500,000 and 394,917 vehicles including motorcycles are registered according to the statistics of 2011. It is known that the number of available parking lots in the city center is about 3500 places. From these data, we assume and set the maximum number of the cars requesting parking (N) as 500 at each simulation unit time (i.e. 1 min), which leads to the maximum 120,000 requests for parking guidance during simulation time (4 h). During the simulation test, totally about 40,000 locations of cars within the city area and their destinations are generated and processed.

To evaluate the performance of the proposed algorithm depending on the variation of the maximum number of the cars requesting parking (N), four kinds of N values (i.e. 50, 100, 300, and 500 cars respectively) in a unit simulation time are considered in simulation. As a result, the number of the cars parking requests is generated based on four kinds of uniform

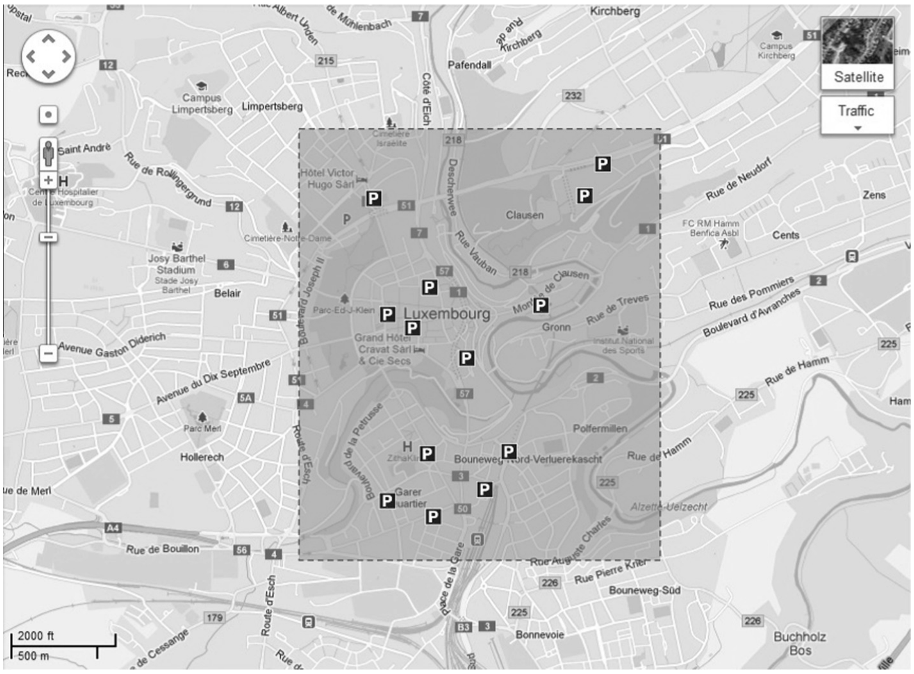

Fig. 3. Target area (10 × 16 km) of simulation test.

Table 2
The number of parking lots of each parking facility.

Parking facility no.	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
Number of parking lots	272	264	150	829	274	214	200	170	282	356	258	93	30
Parking cost (euro/hour)	1.5	1	1.2	1	1	1.5	1.2	1	1.2	1	1	1	1.2

distributions U (0, N) where N = 50, 100, 300 and 500, respectively. The possibility that a driver selects the reservation option in parking guidance is set to 50% arbitrarily. To improve reality, the cars which do not use our parking guidance system are also included in the simulation since it is natural that not all cars will use the proposed smart parking guidance system. These cars occupy free parking lots unexpectedly and affect parking assignment. We assume that it takes at least 10 s entering a parking facility and the maximum number of unexpected occupying cars cannot exceed five cars per minute. Thus, unexpected occupation is modeled based on U (0, 5). In the simulation test, MATLAB is used for the necessary numerical calculation and Google map service is used to estimate the distance and duration for driving and walking. Actually, the provision of reservation option is decided by the threshold value θ so that it is necessary to survey the preference of drivers and to decide appropriate value of it. In this study, the threshold value of *parking utility function for reservation* is arbitrarily set to 1.2. This threshold value is decided by the simulation test in order to provide a certain amount of reservation options. The system operator can adjust this value to increase or decrease the number of provided reservation options (see Table 3).

According to the variance of weighting values used in the parking utility function, the assignment of cars to parking facilities can be varied. The driver's preference is represented by weighting values. For the simplicity, this study deals with three different weighting values: neutral (1), important (2), and very important (3). In the simulation test, six categories according to the driver preference have been tested as shown in Table 4. The six categories include not only one preference that equally emphasizes all factors of the *parking utility function for suggestion* but also five different preferences that emphasize on each factor. Note that the considering system in this problem is the centralized system which provides the best parking place to each car. Hence, drivers do not choose preference since the parking selection is performed and controlled by the central server.

4.3. Result and analysis

During simulation, the number of the cars using parking facilities and the status information of parking facilities such as the capacity of parking facilities and the number of occupied parking lots are randomly generated as shown in Fig. 4.

Fig. 4a shows the random generation of the number of the cars requesting parking at each simulation time during simulation period when N is set to 500 cars. Fig. 4b depicts the number of the parking lots occupied by unexpected cars which arrive at parking facility without using our system and the number of freed parking lots due to leaving from parking facility at each simulation time. These unexpected occupation and inoccupation cases are included in the simulation to improve the reality of simulation. As time goes by, the number of free parking lots becomes decreasing due to the increased parking requests so that the number of occupied parking lots by unexpected cars becomes decreasing. On the contrary, the number of leaving cars is irrelevant with the number of the cars requesting parking so that it shows a typical distribution of uniform random generation. From these graphs, it can be recognized how many cars are processed and how the status of parking lot is changed during simulation.

In this study, the performance of the proposed approach has been assessed by various measures as below.

– **Average driving duration**: This measure indicates the average on driving durations (from current locations to guided parking facilities) of all cars considered in the simulation. The average driving duration is calculated as the sum of all driving durations of guided cars divided by the number of guided cars. The less value of this measure is more desirable in that the redundant consumption of time and energy can be reduced and the harmful effect such as air pollution can be diminished.

Table 3
Simulation parameters.

Simulation parameters	Setting value
– Simulation duration	240 min (4 h)
– The number of cars that unexpectedly occupy parking space per each parking facility without using the proposed system	0–5 cars per one minute (uniformly random)
– The number of cars that unexpectedly leave each parking facility	0–5 cars per one minute (uniformly random)
– Maximum number of the cars concurrently requesting parking guidance per simulation time (N)	50/100/300/500 cars per one minute
– Reservation rate	50%
– Threshold value θ	1.2

Table 4
Weighting factors by preference.

Preference	Parking utility function for reservation		Parking utility function for suggestion		Description
	Weighting factor	Value	Weighting factor	Value	
I	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(2, 2, 2, 2)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$	(2, 2, 2, 2, 2)	– Equally emphasis on all factors
II	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(3, 1, 1, 1)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$	(3, 1, 1, 1, 1)	– Emphasis on the driving duration distance from current location to a parking facility
III	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(1, 3, 1, 1)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$	(1, 3, 1, 1, 1)	– Emphasis on the walking distance from a parking facility to destination
IV	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(1, 1, 3, 1)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$	(1, 1, 3, 1, 1)	– Emphasis on the lower parking cost
V	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(1, 1, 1, 3)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$	(1, 1, 1, 3, 1)	– Emphasis on the avoidance of traffic congestion
VI	$(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$	(1, 1, 1, 3)	$(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$	(1, 1, 1, 1, 3)	– Emphasis on the reduction of parking failures

- **Average walking distance**: The average walking distance is selected as another performance measure to evaluate how far the guided parking facility is located from a driver's destination. The shorter walking distance is mostly preferred by drivers since they want to park near their destinations in order to reduce walking time. The average walking distance is calculated as the sum of walking distances of all drivers in the guided cars divided by the number of guided cars.
- **Parking fail rate**: The driver which does not use reservation option has a possibility to fail to find a free parking lot when he/she arrives at the guided parking facility since the free parking lots have been occupied by other cars while he/she is heading to the guided parking facility. The parking fail makes drivers irritating and not trusting the smart parking guidance system so that it is important to monitor this measure and to try to reduce it. To monitor the parking fail rate at a specific simulation time t, we define a measure to trace the parking fail of the guided cars using Eq. (5), which is called parking fail rate, $F(t)$.

$$F(t) = \frac{\sum_{t^*}\sum_j g_j(t^*)}{t} \tag{5}$$

- An index j represents the parking facility (1 to m) and t^* denotes the simulation time. The $g_j(t^*)$ denotes the number of the cars which fail to find a free parking lot when each car arrives at the guided parking facility j at simulation time t^*. To calculate the parking fail rate, the number of the failed cars at each parking facility until current simulation time t is summed and divided by simulation period t.
- **Parking resource utilization rate**: The proposed parking guidance method is designed not only for drivers' own benefit but also for public benefit. From the viewpoint of public benefit, it is necessary to measure how efficiently the parking guidance can improve public welfare. To check this, the authors define a measure to evaluate the degree of utilization of parking resources in a city. The average of occupied parking lots during simulation is compared with the total capacity of parking lots in a city, which is calculated by Eq. (6).

$$R(t) = \frac{\frac{\sum_{t^*}\sum_j O_j(t^*)}{t}}{\sum_j L_j} \tag{6}$$

- $O_j(t^*)$ denotes the number of occupied parking lots of the parking facility j at simulation time t^*. L_j indicates the total number of the parking lots of parking facility j. According to Eq. (6), $R(t)$ represents the ratio between the average number of occupied parking lots of all parking facilities in a city per simulation time t and the maximum number of parking lots of the city. The higher value of $R(t)$ means that the parking resources in the city are well utilized.
- **Average standard deviation on the number of guided cars to each parking facility**: In the parking assignment, it is also important to avoid traffic congestion caused by parking guidance itself. To assess this objective, the authors calculate the standard deviation on the number of guided cars to each parking facility. The lower value of this measure indicates that the assignment of car is evenly dispersed to each parking facility. This measure is obtained by calculating the average of the standard deviations on the number of the cars guided to each parking facility during simulation.
- **Averaged occupation ratio of parking facility**: To check the degree of the utilization of each parking facility j, averaged occupation ratio of the parking facility j, $S_j(t)$, is defined as Eq. (7). Using this measure, we can estimate how efficiently each parking facility is utilized. $O_j(t^*)$ and L_j is the same as those of parking resource utilization rate.

$$S_j(t) = \frac{\frac{\sum_{t^*} O_j(t^*)}{t}}{L_j} \tag{7}$$

- **Parking facility occupancy rate**: This measure, $Q_j(t)$ shows how much each parking facility is utilized at each simulation time t. The equation is defined as the ratio between the number of occupied parking lots and the full capacity of each parking facility, which is expressed by Eq. (8). $O_j(t)$ and L_j are the same as those of parking resource utilization rate.

$$Q_j(t) = \frac{O_j(t)}{L_j} \tag{8}$$

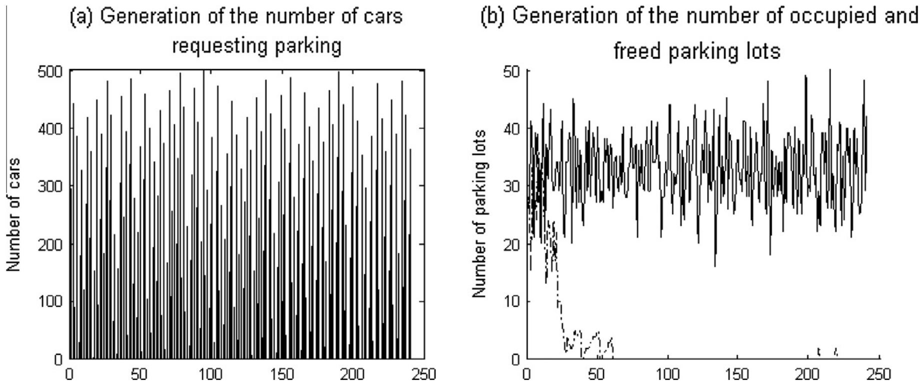

Fig. 4. Data generation of the number of the cars requesting parking and status of parking facilities.

Table 5
Simulation results.

Maximum number of the cars concurrently requesting parking (N)	Preference	Average driving duration (min/car)	Average walking distance (km/car)	Parking fail rate (car/min)	Parking resource utilization rate (%)	Average standard deviation (car)	Total number of guided cars during simulation (with reservation/without reservation)
50	Base case	10.2546	0.58088	0.21635	65.1365	10.2713	(0/4795)
	I	8.9562	0.93383	0.17596	68.2977	4.754	(33/4762)
	II	**7.8363**∗	1.3214	0.1391	67.621	3.9121	(529/4266)
	III	9.7848	**0.6873**∗	**0.**094872∗	68.4737	4.0877	(1778/3017)
	IV	8.9353	0.97206	0.16891	67.9821	5.9811	(5/4790)
	V	8.8923	0.98318	0.14968	66.7667	**2.3126**∗	(166/4629)
	VI	8.9892	1.0473	0.10449	**68.8878**∗	5.9362	(1014/3781)
100	Base case	10.2821	0.58516	0.99519	75.2645	19.9604	(0/9588)
	I	8.8036	0.99179	0.83365	78.9925	8.5694	(29/9559)
	II	**7.8078**∗	1.3468	0.78045	78.8672	7.0497	(578/9010)
	III	9.7305	**0.68941**∗	**0.60801**∗	79.6245	7.4474	(2154/7434)
	IV	8.7452	1.0319	0.86763	80.0634	11.083	(5/9583)
	V	8.668	1.024	0.83333	77.175	**3.9395**∗	(118/9470)
	VI	8.9535	1.1875	0.7266	**82.2465**∗	16.9212	(1339/8249)
300	Base case	10.3301	0.58449	5.9321	89.1979	57.7762	(0/28766)
	I	8.3756	1.023	5.8856	91.1548	18.2532	(23/28743)
	II	**7.5651**∗	1.3879	5.8974	91.3929	19.392	(342/28424)
	III	9.615	**0.66384**∗	**5.7635**∗	92.1003	18.9312	(1166/27600)
	IV	8.3728	1.0528	5.9644	91.4657	29.0575	(3/28763)
	V	8.3866	1.0384	5.8798	90.3937	**7.8478**∗	(51/28715)
	VI	7.8759	1.3239	5.9131	**92.4856**∗	37.6053	(335/28431)
500	Base case	10.3275	0.58454	11.6103	92.389	92.389	(0/47940)
	I	8.3067	1.0318	11.6785	93.6897	27.1335	(25/47915)
	II	**7.5036**∗	1.3946	11.7048	94.0459	31.6239	(335/47605)
	III	9.5934	**0.66118**∗	**11.5471**∗	**94.6999**∗	28.9717	(1183/46757)
	IV	8.3201	1.0597	11.7529	93.8219	47.9596	(2/47938)
	V	8.3316	1.0404	11.6801	93.287	**11.7268**∗	(44/47896)
	VI	7.6711	1.3372	11.7006	94.3028	49.099	(121/47819)

We have run the simulation under six different preference categories as shown in Table 5. For the comparison of the proposed parking guidance algorithm, we have also tested for the base case which assumes the situation that all drivers are heading to the nearest parking facility from their destinations without the use of our system. Table 5 shows the simulation results according to the change of the N values, 50/100/300/500, respectively.

In Table 5, the best performance value for each performance measure is marked with bold character and asterisk. Here, the best performance means the minimum value among simulation results depending on preferences in terms of duration, distance, fail rate, and standard deviation, or the maximum value in terms of utilization rate. Regarding the first performance measure, i.e. *average driving duration*, preference II outperforms other preferences. Preference II puts more value on the factor of driving duration and distance. As designed, the parking facilities which are located closer to requesting cars are suggested to drivers so that the overall driving duration becomes reduced. Compared to the overall driving duration (about 10 min) of the base case, preference II takes less than 3 min as about 7 min of driving. It means that the cars with preference II can save

energy consumption for 3 min driving on average. However, on the contrary, the value of performance measure called *average walking distance* increases as driving duration decreases so that the preference II shows the worst performance for this measure. Regarding the *average walking distance* measure, preference III shows good performance since this preference puts more weight on the factor related with walking distance. When preference III is used in the parking assignment, the walking distance is about 600*m* for each *N* value. On average, the walking distance is about 100*m* longer than that of base case. Compared with other preferences, preference III reduces about 400*m* of walking distance. Furthermore, it is observed that both driving duration and walking distance have no big difference according to the change of *N* values. From this fact, we could guess that the maximum number of the cars requesting parking does not affect the increase or decrease of driving duration and walking distance. However, regarding the *parking fail rate* measure, the failed cars during simulation varies according to the change of *N* values. When the value of *N* is set to 50 cars per simulation time, the best performance is recorded as 0.094872 car per simulation time. However, as the value of *N* increases, the more cars fail to find free parking lots when they arrive. In the fifth column of Table 5, the number of failed cars rises to 11 cars when the value of *N* is 500. Since the number of considered parking facilities in simulation is only thirteen and the available parking lots are limited, it is natural that the number of available free parking lots becomes decreasing as the number of parking requests becomes increasing. It seems that the preferences used in the assignment do not have much effect on the *parking fail rate*. However, overall and especially in the less intensive case, e.g. in the case that the value of *N* is 50, preference III shows relatively good performance compared to others. Generally, preference III shows the better result of *parking fail rate* than that of the base case, which means preference III provides more short walking distance with higher possibility to find free parking lots.

On the other hand, from the viewpoint of a city traffic management, it is important to get the higher value of *parking resource utilization rate* (refer to the sixth column in Table 5). In the simulation result, the preference VI shows good performance of parking lot utilization in general. Since the preference VI focuses on the reduction of parking fail of the arriving car, the parking facility having more free space and rarely used is strongly suggested to drivers. As the result, it seems that the overall utilization increases. Due to this characteristic in the parking assignment, the *parking fail rate* under preference VI also has good performance. Generally, compared to the base case, the parking lot utilization is usually improved. However, the effect of preference VI becomes reduced when the value of *N* becomes increasing. When the value *N* rises to 500 cars, the most available parking lots seem to be already occupied. Thus, it seems that the emphasized factor in preference VI does not give much effect on the assignment. In the case of $N = 500$, the preference III shows the best performance as about 94% of parking lot utilization.

The alleviation of traffic congestion caused by parking guidance itself can be assessed by the performance measure called *average standard deviation*. The low value of this measure represents well-distributed assignment of cars to each parking facility, which helps to alleviate traffic congestion to each parking facility. The defined preference V focuses on this objective and shows the best performance in all cases. The traffic congestion is reduced dramatically under the preference V. Other performance measures also show relatively good results than those of base case, which means that both public and personal benefits could be achieved concurrently under the preference V.

During simulation, some drivers head to parking facilities using reservation option and others head to parking facilities without reservation. Fig. 5a and b shows the number of driving cars on the road according to the use of reservation option under the preference III. The dotted line indicates the moving cars without reservation option and the solid line indicates the moving cars with reservation. The difference of Fig. 5a and b is the maximum number of the cars requesting parking (*N*) at each simulation time. The values of *N* are set to 500 cars in Fig. 5a and 50 cars in Fig. 5b, respectively. Since the value of *N* in Fig. 5a is high, the number of available free parking lots is insufficient to provide reservation space. Hence, only a few cars can use reservation option under this circumstance. On the contrary, Fig. 5b shows that more cars use reservation option than the case in Fig. 5a. It is because there are available free spaces to reserve parking lots in the less number of the cars requesting parking. From this result, it could be concluded that it is difficult to provide reservation option in highly congested and crowded environment.

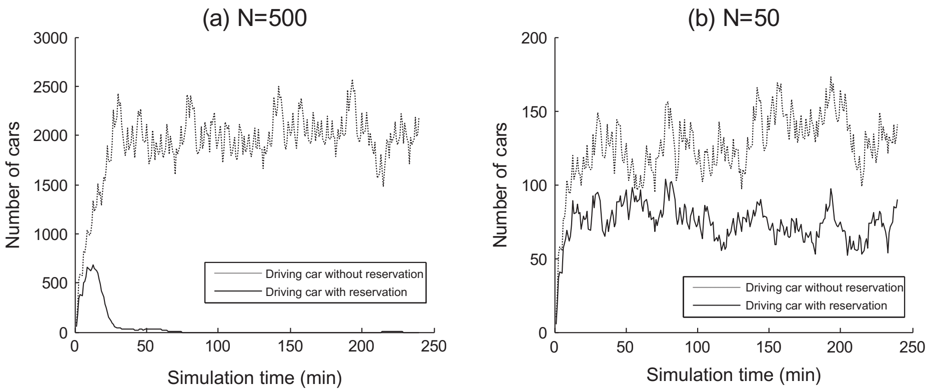

Fig. 5. The number of driving cars with or without reservation.

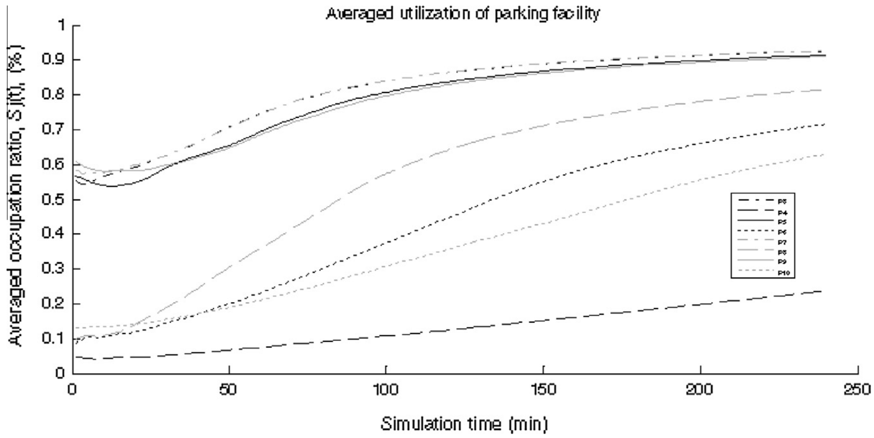

Fig. 6. Utilization of parking facility.

To assess the degree of utilization of each parking facility, it is observed that how many parking lots are occupied. To this end, the percentage of occupied parking lots for each parking facility is calculated using the performance measure *averaged occupation ratio of parking facility*. Fig. 6 shows how much percentage of parking lots at each parking facility is used on average. Fig. 6 shows the case of preference I under $N = 50$. According to Fig. 6, the parking facilities which have more available free spaces have a tendency to show the rapid increasing of utilization rate (e.g. P6, P8, P10, except P4). This is because the parking facilities have the high degree of availability than those of others are highly recommended and occupied.

Fig. 7a shows how much percentage of parking lots of each parking facility is occupied at each simulation time. At the beginning of simulation, there are enough number of available free parking lots. However, as the cars requesting parking are assigned to parking facilities, the occupation rate becomes increased so that the number of failed cars which could not find available parking lots becomes increasing together (see Fig. 7b). Some parking facilities (e.g. P8 and P9) show the higher number of failed cars compared to others. For example, according to Fig. 7a, the parking facilities (P8 and P9) are almost fully occupied after 70 min of simulation time and keep the high value of the occupancy rate, which decreases the possibility to find free space so that the number of failed cars becomes increasing. To improve the reliability of developing system, it seems to be necessary to improve parking assignment so as to reduce the number of failed cars.

Fig. 8 shows the standard deviation on the number of guided cars to each parking facility depending on preferences. Overall, preference V shows good performance since it is designed to avoid the situation in which the cars requesting parking are swarming into only a few parking facilities. As the number of guided cars increases, the standard deviation under preference VI is getting worse. It is because that the emphasized factor in preference VI has not much effect on equalizing the number of guided cars to each parking facility.

During simulation time (total 240 min), the suggestion of parking facility is performed as many as totally 4762 times, which means that several selections are performed at each unit simulation time. For each selection, various factors such as driving distance, walking distance, parking cost, degree of traffic congestion, and degree of availability can be considered as evaluation factors. To see how these factors affect parking selection, the averaged factor values of the selected parking facility that are normalized as between 0 and 1 are drawn in Fig. 9a and b. As shown in Fig. 9a, the values of three evaluation

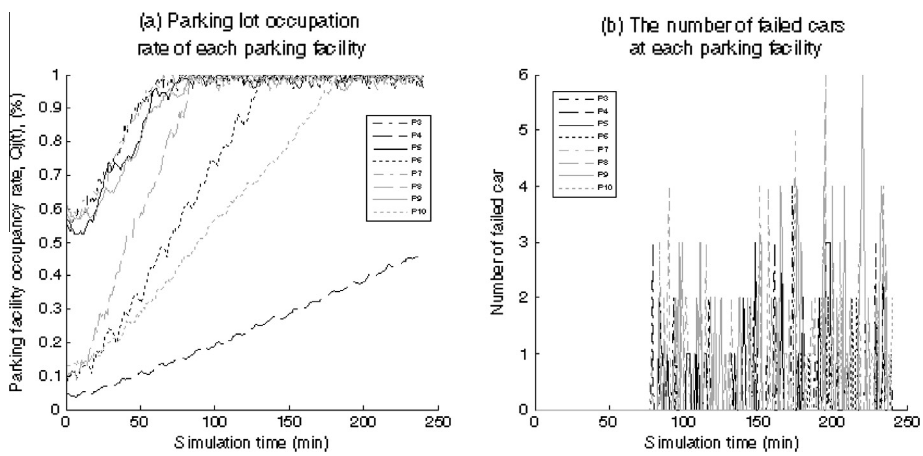

Fig. 7. Parking facility occupation rate.

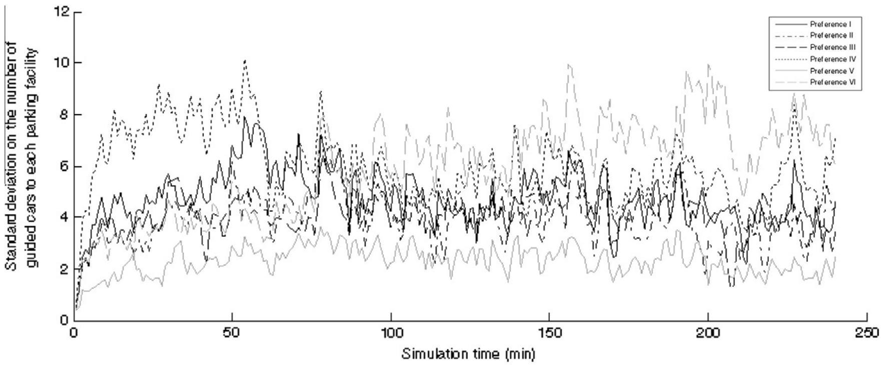

Fig. 8. Standard deviation on the number of guided cars to each parking facility.

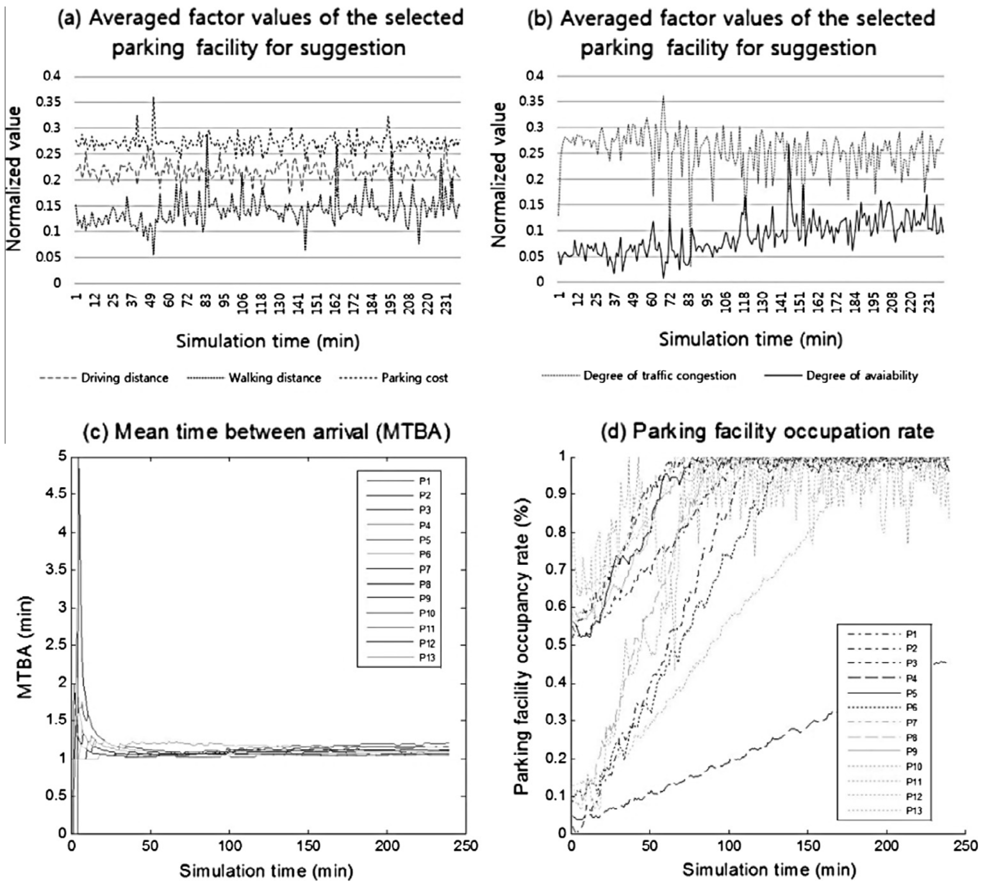

Fig. 9. Parking selection by the *parking utility function for suggestion*.

factors (driving distance, walking distance, and parking cost) show no noticeable trend or characteristics since these factors are not severely affected by the dynamic change of parking facility status. The walking distance becomes slightly increasing since it is not always possible to find the parking place near to destination as the free parking space decreases. In Fig. 9b, the values of the degree of availability have low values in the beginning of simulation and increases as simulation time goes by. According to Eq. (3), the calculation of the degree of availability is affected by the MTBA, the number of free parking lots, and the driving duration. Among them, the driving duration is irrelevant with the current status of parking spaces so that the degree of availability is not much affected by it. However, the MTBA and the number of free parking lots dynamically change according to the status of parking facility utilization. To review the historical change of MTBA, Fig. 9c is depicted. Fig. 9c shows that the MTBA of each parking facility fluctuates in the early stage of simulation and, then, converges to one. As time goes by, the number of guided cars on the road increases and the arrival cars to each parking facility becomes frequent so

that the MTBA converges to near one, which indicates that the cars arrive to the parking facility at almost every unit simulation time. Fig. 9d shows how much each parking facility is occupied. As described in Fig. 9c, the increased number of guided cars reduces the number of free parking lots of each parking facility so that the occupancy rate becomes increasing as shown in Fig. 9d. Considering Eq. (3), the lowered values of the MTBA and the number of free parking lots increase the value of the degree of availability. As shown in Fig. 9c and d, the MTBA and the number of free parking lots are getting decreasing as time goes by so that the degree of availability becomes increasing like Fig. 9b, which means that it is getting difficult to find the free parking lot. On the other hand, in Fig. 9b, the degree of traffic congestion shows decreasing trend in the early stage and stabilized. The degree of traffic congestion is calculated by the number of cars heading to each parking facility (see Eq. (1)). By the utility functions, the car assignments become evenly distributed to each parking facility so that the value of degree of traffic congestion can be stabilized. In summary, Fig. 9 shows that the dynamic change of parking environment including both parking facility and cars have an effect on the evaluation and choice of parking facility.

From the simulation test, the usefulness of the proposed parking guidance method could be verified. The simulation results show that the defined preferences show better performance than the base case. In particular, the preference II guarantees shorter driving duration in all cases. Preference III assures the shortest average walking distance from the guided parking facility to destination. In many cases, preference III also shows the better performance in reducing the number of the cars which fail to find free parking. Using this method, the driving duration, the possibility to find free parking lots when a car arrives, traffic congestion avoidance, parking resource utilization can be improved. Moreover, the proposed algorithm has the low burden of processing so that it can be used for the real-time environment of parking management.

5. Conclusions

This study has introduced the concept of smart parking guidance system and proposed the smart parking guidance algorithm which considers dynamic circumstances of parking facilities in a city and cars on the road. To do this, a heuristic parking guidance algorithm based on dispatching rules used in assigning the cars requesting parking to proper parking facilities is proposed as smart parking guidance algorithm. The proposed dispatching rules have been implemented by two kinds of parking utility functions and parking choice is done by these parking utility functions. The parking utility functions consider various factors related with the decision of parking choice; (1) driving duration and distance, (2) walking distance, (3) parking cost, (4) traffic congestion by guidance itself, and (5) possibility to find free parking lot when a car arrives. To assess the effect of considering factors, six different preferences according to the weights on factors are defined and evaluated. The validation of the proposed algorithm is performed by the simulation tests. For the cases having the different maximum number of concurrent parking requests, six kinds of preferences putting different weights on various decision factors have been evaluated and compared with the base case. Using the proposed algorithm, it has been proven that performance measures such as driving duration and time, the number of failed cars to find free parking lot, utilization of parking resource in city, and traffic congestion can be improved. The proposed system and algorithm enables car drivers to find the most appropriate parking lot and reduce redundant time and energy. Eventually, the redundant time and energy consumption caused by cruising for free parking space in a city can be improved with the help of the smart parking guidance system.

As future research issues, the following could be considered. First, in this study, it is assumed that the system operator can decide weight factor value in the central server manually so that we simplified the degree of weighting factor as three steps. For convenience purpose of human decision, discrete value is more preferable to continuous value. However, theoretically letting weight values have continuous values is not impossible, but to find the best value is another open issue. As a straightforward method, weighting factors can be recalibrated and adjusted up by reflecting the performance of the proposed approach. To maximize the effectiveness of the developing system, it is desirable to adjust weight factors in real-time and automatic way according to traffic and road status. However, the real-time and automatic weighting needs more sophisticated methods, which could be dealt with as a future research issue. Second, if the stay durations for all parked cars are estimated, the utilization and guidance can be more improved. However, it is difficult to know how long the cars will stay at the parking lot and there are cars which do not use the parking guidance system. Hence, we monitor the number of leaving cars which is estimated as uniform random. By setting the number of leaving cars as random number, the staying and leaving of cars are simulated. However, it seems that considering the 'stay-duration' in the algorithm is valuable and interesting point, which could be another future research issue.

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